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Intelligent monitoring for infectious diseases with fuzzy systems and edge computing: A survey

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ABSTRACT

Infectious diseases usually have the characteristics of rapid spread with a large impact range. Once they break out, they will cause a large area of infection, which creates tremendous health and security risks. Thus, early infectious disease monitoring and prevention are critical. Current surveillance systems can predict the incidence of infectious diseases to a certain extent. However, the diversity, inaccuracy and incompleteness of the data collected by sensors make it difficult to obtain accurate monitoring results. Moreover, the limited local resources of a monitoring system cannot process the increasing volume of data in a timely manner. To address these challenges, fuzzy logic and edge computing have been applied to infectious disease monitoring in recent years. This paper presents a comprehensive review of infectious disease monitoring technologies based on fuzzy logic and edge computing. Fuzzy neural networks in infectious disease surveillance are introduced in detail, followed by a brief study of applications of fuzzy systems in infectious disease surveillance. Finally, improvements in existing disease detection systems based on the combination of edge computing and fuzzy logic are described. The review shows that edge computing and fuzzy logic are complementary and that their combination greatly improves the processing efficiency and the storage space of the data. At the same time, with edge computing as the carrier, the combination of fuzzy logic, neural networks, expert systems and other technologies can effectively carry out disease prediction and diagnosis.

1. Introduction

New infectious diseases are characterized by rapid spread and difficult elimination of pathogens. Currently, the vast majority of the world has been affected by COVID-19, causing substantial economic losses and human casualties. The emergence of other infectious viruses also brings health and security risks to human lives [1,2]. Meanwhile, the rapid development of the medical industry is trying to meet the diversified needs of disease prevention and treatments. Against this background, intelligent medical care (IMC) is emerging at this historic moment [3]. Compared with traditional physical medicine, IMC is based on advanced artificial intelligence technologies, connecting patients and hospitals in an organic medical system through the Internet of Things (IoT). Therefore, IMC enables patients to receive various medical services without leaving their homes, which not only increases the concurrent number of patients diagnosed and treated but also effectively collects a large amount of patient data for further treatment investigation. Consequently, IMC has improved the surveillance intensity and the diagnostic efficiency of infectious diseases.

Generally, existing smart healthcare systems are capable of processing only accurate and complete medical data. Data that are missing or uncertain are often discarded. In addition, medical data exist in numerous forms, including numeric, textual reports and images. Medical systems need to translate these different forms of data into a unified standard before they can be processed, which consumes time and energy. To address the deficiency of current medical systems, fuzzy logic was introduced into the medical field. Fuzzy logic uses a membership degree to replace the Boolean truth value. Through membership degree calculation, concepts that cannot be described by deterministic

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language are expressed quantitatively. Therefore, some abstract data and diagnostic language in medicine can be well represented by fuzzy logic [4]. In general, fuzzy logic makes the following contributions to the monitoring and diagnosis of infectious diseases:

- Expertise is introduced into infectious disease surveillance systems. Fuzzy control directly adopts linguistic control rules. Therefore, the control mechanism and strategy are easy to implement [5].
- Fuzzy rules can be used to transform infectious disease data regardless of their characteristics, which greatly improves the utilization rate of the collected data by addressing the missing, uncertain and diverse forms of medical data efficiently [6].
- Fuzzy control makes the control process more able to model human experience through fuzzy rules with language characteristics, which improves the intelligence of infectious disease monitoring [7].
- The original data are transformed through membership functions instead of being uploaded directly, which reduces the possibility of raw data leakage and improves the protection of patient privacy [8].

Existing infectious disease surveillance systems have significantly improved by the introduction of fuzzy logic. According to the survey, many newly developed medical systems have integrated fuzzy logic, mainly through the development of fuzzy expert systems, to improve the accuracy of disease diagnosis and treatment. Although there are few examples of combining fuzzy logic with specific technologies, the trend is growing. Currently, fuzzy neural networks and other technologies are often used in medical data processing and analysis. Nevertheless, the computing resources of infectious disease surveillance systems are limited [9]. As the scale of infectious disease data grows, processing all data collected by the sensors locally may lead to intolerable delays. As one feasible solution to this contradiction, edge computing places edge servers on roadside units (RSUs) to distribute computing resources originally concentrated in the cloud to the side near users of the infectious disease surveillance system [10,11]. Therefore, the distance between the users of the infectious disease surveillance system and the computing resources can be greatly decreased, along with the latency of the services obtained [12]. In view of this benefit, a large number of cases have used edge computing to monitor infectious diseases [13,14].

A large number of infectious disease monitoring strategies based on fuzzy systems have been studied [15]. To systematically compare and summarize these strategies, this paper conducts a comprehensive and concrete survey of recent research on fuzzy-based infectious disease monitoring systems. Additionally, research on the combination of edge computing and fuzzy logic for infectious disease surveillance is reviewed to generate ideas for the future prevention and treatment of infectious diseases. In this paper, we adopt the research strategy of induction, contrast and summary. First, some popular technologies based on fuzzy logic were listed, and improvements in these technologies by fuzzy logic is discussed. Then, the applications and achievements of fuzzy logic in the medical field are summarized. Finally, combining fuzzy logic with edge computing, which is a popular new computing paradigm, this paper summarizes their complementary advantages and identifies future challenges regarding their application.

The remainder of the paper is organized as follows. In Section 2, technologies based on fuzzy systems are summarized. In Section 3, applications of fuzzy systems in infectious disease monitoring are presented. Then, infectious disease monitoring based on edge computing and fuzzy systems is introduced in Section 4. Future expectations and challenges are provided in Section 5. Finally, Section 6 concludes the paper.

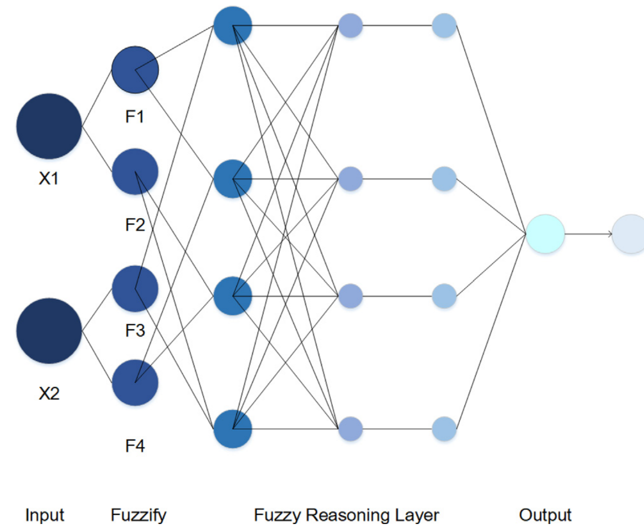

Fig. 1. The Structure of FNN.

2. Technologies based on fuzzy systems

In the medical field, the prevention and treatment of infectious diseases can be approximately divided into two categories. The first category is macro prediction and target tracking with big data, and the second category is patient diagnosis and treatment. Infectious disease detection is often designed over a wide range of cases and on a large scale, requiring the use of artificial intelligence and computer assistance. However, when incorporating a large amount of expert experience and scattered datasets, the accuracy of traditional deep learning algorithms is often low. Fuzzy systems make it possible to describe a vague concept to computers. We summarize two types of techniques based on fuzzy logic from the prediction and diagnosis of infectious diseases: (i) specific methodologies that include fuzzy neural networks (FNNs) [16] and fuzzy comprehensive evaluation (FCE) [17] and (ii) the combination of fuzzy logic with control systems and expert systems, including fuzzy control (FC) [18] and fuzzy expert systems (FESs) [19].

2.1. Fuzzy neural network

The fuzzy system and neural network are combined into the FNN, which has better computing performance and a wider range of information processing capabilities [20]. Different from traditional neural network models, all the parameters in the FNN have physical meanings. In certain areas, the meanings of the parameters are of great significance and can offer tremendous information. For example, doctors usually need to tell patients the cause of diseases and possible complications. However, this information is not available in traditional neural networks. Commonly, we can summarize the structure of the FNN as shown in Fig. 1 [16]:

The function of Layer-1 is to input the data, and the function of Layer-5 is to output the processed data. Layer-2 completes the fuzzification of the input data. The weights from layer-1 to layer-2 are 1, and the offsets are all 0. Taking Fig. 1 as an example, we assume that the nodes in layer-1 correspond to the m and n fuzzy sets. To present all the $m \times n$ rules, every node in layer-3 needs to connect to one of the m nodes and one of the n nodes. The nodes in Layer-4 are fully connected to the nodes in layer-3 and save the maximum products of the corresponding node's value. Finally, according to the output of layer 4, we can obtain a clear result with the centroid method [16]. To conclude, we can fuzzify the input and realize fuzzy reasoning and clear output with the FNN. Compared with traditional neural networks, the FNN makes the process of learning comprehensible and more efficient. Thus, we can predict the trend of epidemic diseases more accurately and take measures to contain them in a timely manner.

In fact, due to different needs, the establishment of the fuzzy neural network model is also different, sometimes requiring a high precision model and sometimes requiring a model as simple as possible. Typical fuzzy neural networks include BP fuzzy neural networks, adaptive neural fuzzy inference systems (ANFIS), B-spline fuzzy neural networks and RBF fuzzy neural networks. By using rough set theory, these networks are suitable for processing fuzzy datasets or real-time data streams generated with missing data or image segments [21]. For example, using fuzzy neural networks to process pedestrian data collected by roadside sensors predicts the trend of infectious disease circulations and the probability of outbreaks more accurately and efficiently [22]. At the same time, the new optimization algorithms make the structure of the FNNs more variable to cope with real-time changing application scenarios. In [23], Jun et al. proposed an IT2 fuzzy classifier by leveraging the dynamic adjustment mechanism of error and incentive. By constructing the uncertain footprint, this method can effectively blur the uncertain characteristics of medical and other industry data and further optimize the classification or prediction results. Bin et al. integrated gene expression programming into interval type 2 fuzzy neural networks to increase the flexibility of network structures [24]. This method can significantly improve the accuracy and convergence of networks.

2.2. Fuzzy comprehensive evaluation

Fuzzy comprehensive evaluation (FCE) is a method that helps evaluate events in a fuzzy way when the characteristics of the events are not conveniently described in precise quantities. FCE can imitate human fuzziness and positiveness, thus helping evaluate events qualitatively and quantitatively [17].

$$U = \{u_1, u_2, u_3, u_4, \ldots\ldots, u_n\}, \tag{1}$$

$$V = \{v_1, v_2, v_3, v_4, \ldots\ldots, v_m\}, \tag{2}$$

$$W = \{w_1, w_2, w_3, w_4, \ldots\ldots, w_n\}, \tag{3}$$

$$R = \begin{pmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{n1} & \cdots & r_{mn} \end{pmatrix}, \tag{4}$$

$$Y = W \cdot R = \begin{pmatrix} w_1 & w_2 & \cdots & w_n \end{pmatrix} \cdot \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{pmatrix} = \begin{pmatrix} y_1 & y_2 & \cdots & y_m \end{pmatrix}. \tag{5}$$

First, the FCE method constructs a set U containing every evaluation indicator and a set V containing every decision result. Second, we need to determine the weighting coefficient matrix W of every influencing indicator. In the fuzzy matrix R, r_{ij} stands for the degree of each indicator's contribution to every evaluation result. The comprehensive evaluation matrix Y consists of the products of matrix W and matrix R. Y represents the probability that the object belongs to every evaluation case. Finally, we obtain the result by virtue of the maximum membership principle. Namely, the result is the maximum of matrix Y. When using the multilevel model of PCE, we usually divide the set U into several parts and process each level as above [25].

In the process of FCE, weights symbolize the degrees of importance of every evaluation indicator, thus significantly influencing the accuracy of the models' descriptions. Therefore, determining the weights is so critical that there are many methods to guarantee model rationality and accuracy, such as weighted statistical methods, expert estimation methods, the analytic hierarchy process (AHP), Delphi methods and frequency statistic methods. In practice, AHP is used more frequently because it is flexible, systematic and easy to understand [26].

Through the application of the fuzzy matrix and the coefficient matrix, FCE helps make scientific and reasonable decisions [27]. Additionally, we should pay close attention to the determination of weighting coefficients, membership functions and algorithms since small changes in them could greatly influence the whole model.

2.3. Fuzzy control

In the medical field, especially with respect to epidemic diseases, traditional controllers are gradually becoming unable to perform monitoring tasks as expected. Commonly, the structure of fuzzy control can be divided into four pieces: the input device, fuzzy controller, controlled object and sensor [28]. The input device accepts the information and turns it into an analogue signal, which can be identified by computers. As the core of the whole system, it uses fuzzy theory to process information and produce clear results. Controlled objects need to be modelled in different ways according to their characteristics. For example, in the field of epidemic diseases, most problems are nonlinear. Therefore, the key issue relates to finding the appropriate nonlinear model. Sensors cannot be too sensitive and accurate because they transform physical information to electronic information, so tiny changes make a difference.

Owing to its excellent ability to solve problems that are difficult to describe by precise mathematics, fuzzy control can realize the effectual control of objects that cannot be modelled as precise models. Based on fuzzy mathematics, fuzzy set theory and fuzzy language, fuzzy control has the characteristics shown in Table 1:

To achieve more objectives in various fields, fuzzy control has been combined with many other technologies, some of which are listed in Table 2.

Fuzzy control is meant to be applied in the monitoring of epidemic diseases and scheduling of relevant medical materials. However, there is a restricted relation between the operation speed and the control precision. Therefore, its practical application still needs to be developed in critical situations [18].

2.4. Fuzzy expert systems

As an improved expert system combined with a fuzzy system, a fuzzy expert system (FES) is able to model fuzzy things and obtain a similar conclusion to experts. Based on expert experience and other known knowledge, a FES usually focuses on specific fields. Commonly, it consists of six parts: a fuzzy knowledge base, fuzzy reasoning machine, fuzzy comprehensive database, fuzzy knowledge acquisition machine, system interpreter and man–machine interface. Among them, the fuzzy knowledge base and fuzzy reasoning machine are the core of the FES [29].

Table 1
Advantages of fuzzy control.

Advantages	Description
High operability	The system is easily operated by predicting human experience.
Robust	The system is only slightly influenced by outside interferences and coefficient changes.
Good associativity	The system can be combined with another mature control theory.
Wide application range	Fuzzy control is suitable for objects whose status changes significantly and whose features are difficult to identify.
Language controlling rule	Fuzzy control is based on expert knowledge and data, so it does not need accurate models.

Table 2
Technologies combined with fuzzy control and their highlights.

Technologies	Highlights
Genetic algorithm	Good at processing nonlinear problems, self-organization, self-learning, and self-correction.
Rough set	Strengthens the ability of classifying and complete self-learning by genetic algorithm.
Neural network	Good function approximation ability helps realize self-organizing control.
Expert system	Improves the intelligent level and provides better systematic data processing capability.
Chaos control	Enables good short-term prediction with high precision and solves the problems of effective control when the interference of objects keep changing.
Multi-mode variable intelligent control	Improves robustness to the uncertainty of the models and outside interference.

Table 3
Advantages and disadvantages of the four representation methods.

Methods	Advantages	Disadvantages
Frame notation	Naturally and intuitively, it could portray the inside connection of knowledge and has good inheritance just like the human brain.	It is not easy to apply because of its rigidity.
First-order predicate logic representation	It is easy and natural to realize.	The low efficiency of this method makes is difficult to describe procedural knowledge and be fuzzy.
Semantic network representation	It is easy to interpret as well as understand, and its application is convenient.	Its limitations and complexity require more research.
Production notation	This method could process fuzzy knowledge and is easy to modify.	Its drawback is its low efficiency.

The four knowledge representation methods are frequently used: (i) Frame notation. This structured system is made up of slots, and every slot consists of several sides that describe different attributes of events. (ii) First-order predicate logic representation. The highly formalized system could accurately represent the human mind. It uses predicate formulas made up of predicates containing practical meanings of knowledge. (iii) Semantic network representation. In the structured system, dots are the mapping of events, and their attributes and arcs describe their relationship. (iv) Production notation. Similar to the "if-then" rule, it is heuristic and flexible with more kinds of input. The advantages and disadvantages of these methods are listed in Table 3.

In terms of the reasoning method, the usage of fuzzy logic and synthetic methods is similar to what is mentioned above in terms of FCE.

Facilitated by a fuzzy system, an expert system can process a wider range of information and become more flexible when reasoning. FES now simulates the human mind more closely, and thus, it can complete more tasks than experts and with even better performance. For example, FES could help doctors reduce their stress and boost their efficiency when treating common diseases so that doctors have more time and energy for other diseases. Nevertheless, there are still many problems to be resolve, such as the poor ability to create knowledge, relying too much on experience, and monotonicity of reasoning.

3. Applications of fuzzy systems in infectious disease monitoring

In this section, the applications of fuzzy systems in infectious disease monitoring are introduced. They involve disease prediction and disease diagnosis. Disease prediction refers to the prediction of future risk and incidence of infectious diseases in an area based on information such as the movement and the current number of infected people to facilitate taking countermeasures in advance. Disease diagnosis refers to determining whether a person is suffering from a disease based on the physical symptoms of the person being treated to improve the confirmation rate and achieve accurate treatment. Therefore, the accuracy of disease prediction and diagnosis is very important for disease prevention and control.

3.1. Fuzzy systems in epidemic disease prediction

3.1.1. Prediction of Adaptive Neuro-Fuzzy Inference System (ANFIS)

The adaptive neuro-fuzzy inference system presented by JS.R. Jang is a new kind of fuzzy inference system structure that organically combines neural networks and fuzzy logic. It adopts a hybrid algorithm of least squares and backpropagation to adjust the conclusions premising parameters and is able to generate "If-Then" rules automatically.

COVID-19 is a new type of virus that is generally susceptible to social infection. It is vital to predict the peak and infection cases of COVID-19 to control and prevent infectious diseases. In 2021, Rajagopal et al. presented a machine learning technique based on the ANFIS for the prediction of the possible COVID-19 outbreak in India [30]. The system inputs new cases and deaths of India's new crown as a set of datasets. It also evaluates and inputs India's local dataset, including cardiovascular disease, age factor, population density, the total population and health care facilities. Finally, the performance of the new dataset and test dataset obtained after ANFIS training are evaluated, and a new prediction dataset is generated, which effectively tracked the growth of the COVID-19 epidemic with an accuracy of 86% [31]. Both systems above provide vital information for the government and society for the prevention and control of the COVID-19 epidemic.

The prediction process of the adaptive neuro-fuzzy inference system is shown in Fig. 2.

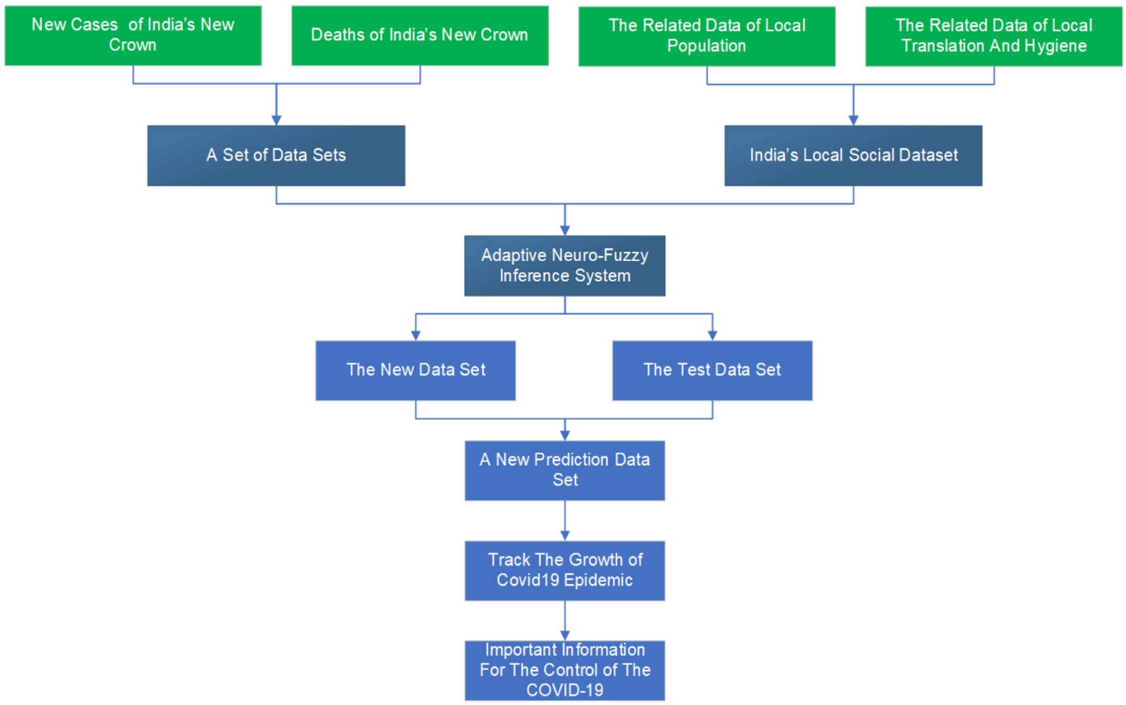

Fig. 2. Prediction of adaptive neuro-fuzzy inference system.

3.1.2. Prediction of the rule based fuzzy logic system

The information in the system based on fuzzy rules is usually represented by IF-THEN statements. Rule-based fuzzy logic consists of two parts: the first part is the related condition, called the inward variable, and the second part is the outward variable [32].

COVID-19 is highly infectious and dangerous, so the government and individuals should strictly implement appropriate measures. In 2020, Cihan used a fuzzy rule-based system to predict the number of COVID-19 daily cases. The input variables of this system are the count of daily deaths d, the total count of intubated patients I, the count of daily examinations R, the count of daily recoveries r, and the total count of intensive care patients P. The study used samples of 124 days. The Wang–Mendel neuro-fuzzy rule inference method is used to process these actual data, and a model for estimating the number of cases per day is established. After training the model with approximately 70% of the dataset (86 days), the number of cases in 38 days (approximately 30% of the dataset) was estimated. By anticipating short-term cases in the future, the government can formulate appropriate policies to control and prevent infectious diseases [33]. In the same year, Painuli developed a system based on fuzzy rule, which is used with MATLAB tools for simulations to give predictions related to whether one is suffering from COVID-19. The system takes age, sex, fever, dry cough, respiratory problems, influenza and medical history of some infected patients as input variables and compares them with the symptoms of the COVID-19 virus published by the World Health Organization (WHO) to predict whether individuals have COVID-19, which is a great help for personal prevention of COVID-19 [34]. The prediction of the rule-based fuzzy logic system is shown in Fig. 3.

3.1.3. Prediction of the Fuzzy Cognitive Map technique (FCM)

A fuzzy cognitive map (FCM) is a modelling technology. It defines the relationship between internal and external variables using previous knowledge and experience.

Pulmonary infection is a serious disease that harms the human body and highly infectious, so it is very important to predict the state of patients. In 2009, Elpiniki et al. proposed an infectious disease prediction tool based on a fuzzy cognitive map, and through the solution of relevant modelling problems and the evaluation of medical tasks that are used to make decisions by FCM, the predictive results of the severity of pulmonary infection are output [35]. Furthermore, in 2012, Elpiniki et al. presented a system with FCM combined with the evolutionary-learning-process genotype. The prediction error calculated was lower. The new evolutionary FCM approach solves the problem of time series prediction [36] (see Table 4).

3.2. Fuzzy systems in epidemic disease diagnosis

3.2.1. Fuzzy Inference Systems (FIS) for diagnosis

A fuzzy inference system is a system capable of processing fuzzy information based on fuzzy inference technology and fuzzy set theory. A fuzzy inference system is able to map internal variables to external variables [37,38]. The fuzzy reasoning process involves three key concepts: the reasoning procedure, membership function and fuzzy set operation [39]. A fuzzy inference system can be divided into the following four points: defuzzification, assessment of inference procedures, weighting, and fuzzification [40].

Dengue fever is an acute infectious disease caused by the transmission of dengue virus through mosquito vectors and is considered a serious disease that threatens human life. Therefore, early diagnosis is very important. In 2016, Saikia et al. designed an expert system to diagnose dengue fever early on using a fuzzy inference system (FIS), which is a powerful tool under conditions of uncertainty and imprecision. A FIS can take the patient's medical test reports and physical symptoms as input variables and convert them into fuzzy membership functions to diagnose dengue fever patients early. The output is the diagnosis result of dengue fever, which can help dengue fever patients take appropriate treatment measures before reaching the complex stage of dengue fever. This method facilitates patient management and reduces the spread and scale of dengue virus in the community [41]. However, the process of diagnosis requires both precise physical examination results and detailed

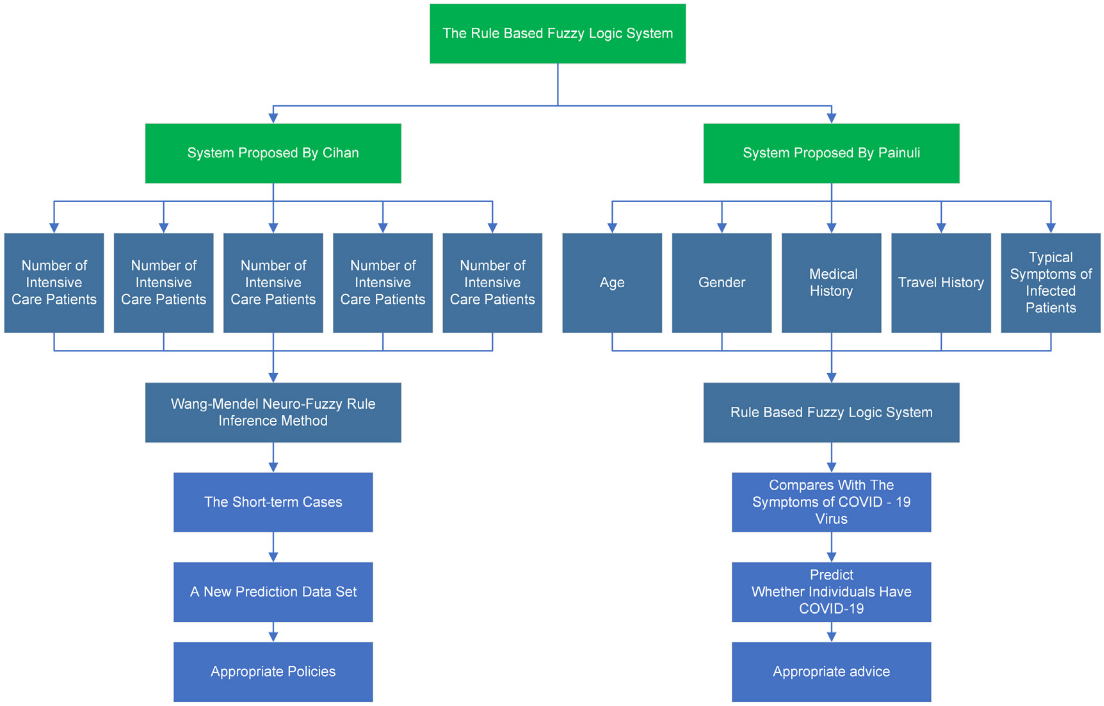

Fig. 3. Prediction of the rule based fuzzy logic system.

Table 4
Main fuzzy systems proposed to enable epidemic disease prediction.

Technique	Highlights	References
Adaptive neuro-fuzzy inference system	(1) Accurately predict the number of infections in a short period of time (2) Provide strategies for the	[30,31]
The rule based fuzzy logic system	(1) Multiple factors referenced to ensure accurate prediction results (2) Provide individuals with infectious disease prediction tools	[32–34]
The fuzzy cognitive map technique	(1) Predict the severity of infectious diseases	[35,36]

physical symptoms, which are not possible in remote areas. Thus, Mubarak (2019) proposed a hierarchical fuzzy inference system (HFIS). The system is simpler and more scalable and can be used for dengue diagnosis. In this system, variables controlling dengue fever are gathered into three fuzzy submodules. The first level of the HFIS model proposed above is represented by these three different submodules. The output of the three modules works as the input to the second-level submodule and produces a real number showing the probability of the presence of dengue fever [42].

Fig. 4 shows the diagnosis of fuzzy inference systems.

3.2.2. Diagnosis of ANFIS

The ANFIS can also be used to diagnose infectious diseases.

Hepatitis is a serious disease, and the most common cause is viral infections, which often occur without a clear cause. It is challenging for doctors to diagnose, and more than one million people worldwide are estimated to die from viral infections every year. Therefore, Dogantekin et al. designed an automatic system for hepatitis diagnosis based on an adaptive neuro-fuzzy inference system (ANFIS) and linear discriminant analysis (LDA). The automatic system uses a combination of classification and feature extraction. It is divided into two main stages, classification and feature extraction dimensionality reduction. Feature extraction involves extracting the features of hepatitis from the UCI knowledge base of the machine learning database. Then, dimensionality reduction is performed, and LDA is used to reduce these features from 19 to 8. Finally, the classification stage inputs the reduced-dimensional features into the ANFIS classifier for related classification. The accuracy of the LDA-ANFIS diagnosis system for classification is 94.16% [43], which is more advanced than many other methods [44,45]. However, it does not support incremental learning. Therefore, Mehrbakhsh et al. developed a method for data dimensionality reduction based on nonlinear iterative partial least squares, self-organizing mapping technology for clustering, and neuro-fuzzy inference system integration for hepatitis diagnosis. This method makes full use of the advantages of integrated learning. It optimizes the efficiency of hepatitis diagnosis and improves memory requirements. The accuracy of the method on a real dataset obtained from UCI as measured by ROC was 93.06% [46].

3.2.3. Diagnosis of the rule based fuzzy logic system

The rule-based fuzzy logic system can also be used to diagnose infectious diseases.

Tuberculosis is a chronic disease with persistent disease and is difficult to diagnose. Once the infection occurs, if it is not treated in a timely, nonstandard and complete manner, there will eventually be relapse, deterioration and resistance. Eventually, it will cause death due to repeated hair colouring. In 2011, Semogan et al. presented a system for clinical decision support combining the rule-based fuzzy logic system. Fever duration, nasal phlegm, cough duration, cough, sputum discoloration, afternoon chills, body temperature, night sweating, weight loss and loss of appetite are all input variables in this system to help diagnose different types of tuberculosis, which is very helpful for

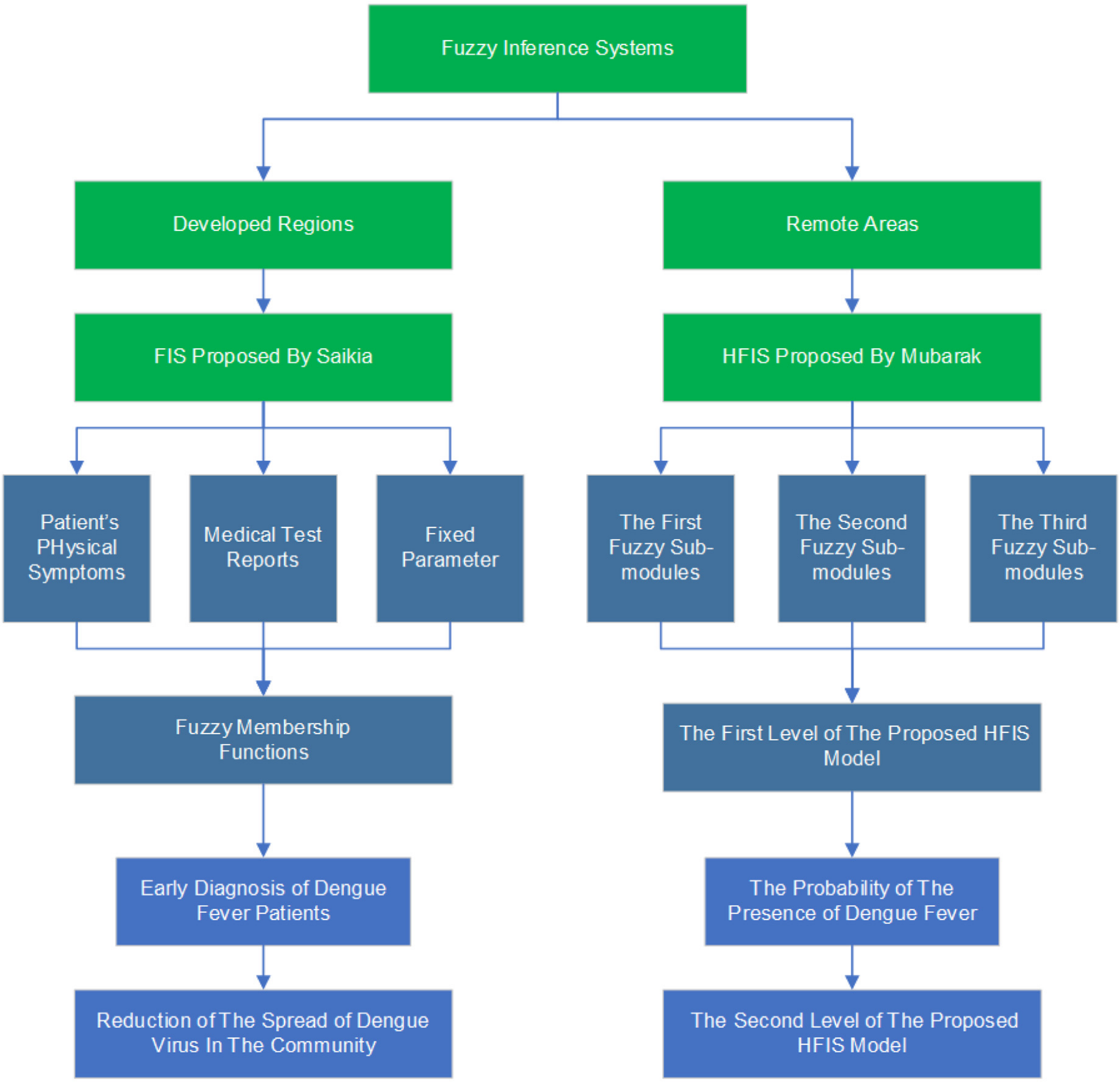

Fig. 4. Diagnosis of fuzzy inference systems.

Table 5
Main fuzzy systems proposed for epidemic disease diagnosis.

Technique	Highlights	References
Fuzzy inference systems	(1) Addresses imprecision and uncertainty (2) Simplicity and scalability	[41,42]
Adaptive neuro-fuzzy inference system	(1) High classification accuracy (2) Support incremental learning and increase memory requirements	[43,46]
The rule based fuzzy logic system	(1) Diagnose different types of infectious diseases (2) Learn the diagnosis of different diseases online	[47,48]

pulmonary doctors in making a diagnosis and is able to reduce diagnostic generation time [47]. Zainab et al. (2018) proposed a fuzzy rule-based expert system (FRS) to diagnose epidemic diseases such as cholera, typhoid, malaria, and hepatitis. The knowledge used in this system is obtained through expert interviews and expressed by production rules (if-then method), and fuzzy logic combines intelligent decision-making with expert feedback, which has good diagnostic performance with 82.3% accuracy and an 85.7% F-score. In addition, the system is able to learn how to diagnose different infectious diseases online and has good scalability [48] (see Table 5).

4. Infection disease monitoring with edge computing and fuzzy systems

4.1. Edge computing with fuzzy systems

4.1.1. Concept of edge computing

Edge computing (EC) is a computing paradigm where computation can be performed at the edge of the network [49]. In EC, computational resources can be positioned at the edge of the network, which is close to users. An "edge" is considered as any storage and computing resource along the path between users and remote computing centres [50]. In [51], EC is also viewed as a distributed computing mode that enables solving main tasks by transferring computing resources and services closer to users [52]. Considering these advantages, EC can be applied in fields such as smart cities, the internet of vehicles and intelligent healthcare [53].

However, as a new computing paradigm, EC not only provides high-quality service for users but also addresses the challenges of the explosive growth of service requests and data storage. The storage capacity and computing resources of edge servers are often limited. At the same time, in the context of the Internet of Everything, ensuring the security of user data privacy has become a problem. Fuzzy logic has a good ability to remove noise. Thus, when processing image datasets, it can effectively remove redundant data and retain key information to improve the processing capacity and storage efficiency of edge computing data. Fuzzy logic also requires powerful storage and computing facilities to store fuzzy rules and perform a series of control flows and operations. EC meets this requirement [54]. The following content will introduce a new method to optimize EC.

4.2. The relationship between edge computing and fuzzy systems

Edge computing has been introduced as a sustainable and innovative new technology to address the greater demand for mobile network services due to ever-increasing mobile network traffic. However, with the explosive growth in smart terminal devices, data should also be preprocessed while computing power is improved. Some current data preprocessing methods include data cleaning [55] and data reduction [56]. In addition, fuzzy computing can be used for data preprocessing. The fuzzy system converts the input value into the value of the field in an appropriate proportion and uses the spoken variable to describe the measured physical quantity. Therefore, the fuzzy calculation can perform fuzzy preprocessing on the data obtained from different terminals so that these data appear in the same target form. It is convenient for implementing edge computing, which solves the problem of different data sources on an edge node and thus addresses the missing, uncertain and diverse data problems in edge computing. In addition, since edge nodes have weaker computing power and lower storage performance than cloud centres, they are vulnerable to malicious attacks. Some current studies use mutual protection and protocols between nodes to prevent attacks, but fuzzy theory provides a new direction [57]: encrypting data by fuzzing. Rathore et al. proposed a new solution to the multicriteria decision-making problem based on a SHFRS, which applies a fuzzy system to make a good security service selection decision [58]. On the other hand, edge computing also facilitates the implementation of fuzzy theory. Due to the explosive growth in the number of intelligent terminal devices, it is impossible to perform large-scale fuzzy computing on all devices, and the delay caused by transmission to the cloud is unbearable for some service applications. However, the emergence of edge computing has generated ideas. By setting up a large-scale fuzzy system on the edge device, EC can not only process different types and different forms of original data but also transmit fuzzy data to the cloud centre. The latency is greatly reduced, and the energy consumption can also be reduced. In summary, edge computing and fuzzy systems are mutually reinforcing and complementary. Combining them may solve the security problem of edge nodes and may greatly reduce communication delays and energy consumption.

4.2.1. Improvements to edge computing by fuzzy systems

In [59], fuzzy logic is viewed as an extension of many-valued logic, which focuses on handling approximate modes of reasoning instead of precise ones; in other words, everything in fuzzy logic will be defined as a degree rather than 'True' or 'False' in contrast to a classical logical system. By applying a fuzzy system in EC, EC can be optimized in the following aspects:

- Computing efficiency: Deterministic and stochastic models need massive data and information for training to reduce the possibility of applying a false model to practical issues. However, models such as linear programming are determined by only a few restrictions, and excessive input will waste computing resources in this condition. In [60], Rommelfanger proposed fuzzy linear programming based on aspiration levels. Similarly, in EC, by focusing on the main restrictions and leaving the other information collected rather fuzzy, we can reduce the time spent collecting and processing data; thus, computing efficiency can be enhanced significantly.
- Energy consumption: Content caching is a main characteristic of EC, and each content router has the ability to cache; however, these routers consume a large amount of energy, which needs to be handled [61]. Mehamel et al. [62] proposed a caching technique based on fuzzy logic, which considered energy efficiency. This technique offered a new caching strategy that selected fuzzy rules from a fuzzy knowledge base, and the selected standard is the minimum energy consumption. Then, it determined a caching priority degree to each request based on fuzzy logic by considering the frequency, delay and size of the data. This technique helps make decisions and effectively reduces energy consumption.
- Privacy and Security: Considering the mobility of smart devices, the communication between edge servers and mobile devices is unstable, and data can be sealed easily and modified maliciously [63]. Additionally, edge servers are easily attacked because of their fragile defence systems [64]. Therefore, we need techniques based on fuzzy systems to help protect users' privacy and enhance security in the process of data transmission. Mansour et al. [65] proposed a three-tier trust management framework that assessed service providers' credibility. This technique was divided into two stages. In stage I, the three-tier trust management framework evaluated service providers by service performance, their compliance with the service agreement and their violation behaviours. In stage II, by calculating the integration of the three tiers and inputting it into the trust fuzzy inference system based on fuzzy logic, the providers' entire trust value can be obtained. In [66], Sharma et al. proposed a lightweight differential privacy framework that used a fuzzy convolution neural network [67]. The experiment showed that this framework is practical and effective in guaranteeing users' privacy and security.
- Quality of Service (QoS): Considering that edge devices' computing resources are limited, applying an easy computing paradigm and maximizing the share of resource computation help enhance QoS. In [68], Hossain et al. proposed a collaborative task offloading scheme based on a fuzzy system. In this scheme, the delay sensitivity was defined as a fuzzy input parameter, and then the scheme determined the place of task offloading according to fuzzy rules. This scheme showed excellent performance in reducing the average computing time and minimizing the average failure rate; consequently, the QoS showed a remarkable improvement.

Table 6 shows the optimization of the fuzzy system to EC.

4.3. Edge computing with fuzzy systems in the medical field

4.3.1. Advantages of EC with fuzzy systems in the medical field

With the surge in the number of people seeking health care and the frequent outbreak of an epidemic, the tendency to develop smart healthcare is inevitable. Zhu et al. [69] pointed out that the development of healthcare would shift from medical

Table 6
Optimization of fuzzy system to EC.

Optimized performance	Disadvantages of traditional methods	Examples	References
Computing efficiency	Models such as linear programming are only determined by few restrictions, while traditional methods use massive computing resources for training	Rommelfanger proposed fuzzy linear programming based on aspiration levels	[60]
Energy consumption	In EC, each content router has the ability of caching; however, these routers will consume large amounts of energy	Mehamel et al proposed a fuzzy-based energy-efficient caching technique	[61,62]
Privacy and Security	The communication between the edge server and the mobile device is unstable due to the mobility of smart devices. Edge servers are easily attacked because of their fragile defence systems	Mansour et al. proposed a three-tier trust management framework that assessed service providers' credibility. Sharma et al. proposed a light-weight differential privacy framework based on a fuzzy convolution neural network	[64,65,67]
Quality of Service (QoS)	Edge devices' computing resources are limited, while current methods cannot reduce computation significantly	Hossain et al. proposed a novel collaborative task offloading scheme based on a fuzzy system	[68]

treatment to the management of health conditions. In other words, smart healthcare will focus on the monitoring and prediction of health conditions. However, it is unavoidable that in smart healthcare, numerous users will generate a mass of data. Fortunately, by offloading the raw data to edge servers, EC can relieve the workloads of local devices and reduce delays. Certainly, EC cannot completely solve problems such as uncertain input data and complex computation of medical data. Therefore, EC with a fuzzy system has been applied to resolve various open issues.

- Handling uncertain and imprecise input: Considering that data collected from healthcare have different formats and various degrees of accuracy, traditional models view handling these data as a difficult problem. However, such uncertainty and incompleteness could be solved by a fuzzy system. Li et al. [70] aggregated fuzzy and imprecise linguistic information by developing some geometric aggregation operators. Based on the operators, they then proposed a method that helps make decisions. Because people may give an imprecise description of their health condition, this method, which addressed the problem of imprecise linguistic information, worked.
- Offering real-time information: EC with a fuzzy system may play an important role in preventing and controlling epidemic diseases because it can offer real-time information about the pandemic transmission rate and the trace of suspected cases. In [71], Ndii built a model based on fuzzy logic. This model estimated the transmission rate and carrying capacity and then obtained a degree of vaccination coverage level that nearly prevented an epidemic of rabies. In this way, edge devices enable the renewal of the local transmission rate and reasonable vaccination coverage level in real time, thus providing decision makers with adequate information and time to make decisions.
- Using family epidemic prevention experience: During the current pandemic, it seems that the only way that common people can fight the pandemic is to quarantine at home. However, EC with a fuzzy system enables people to contribute their abilities in other unique ways. Fu et al. [72] proposed a fuzzy-based design method that combined factors such as familial anti-epidemic products, anti-epidemic performance and environmental benefits into consideration and then analysed and processed these data based on fuzzy logic programming. The outputs could help design and develop anti-epidemic products. By using this technique, each user can upload data on familial anti-epidemic 'product performance and product parameters to edge servers for further computation; therefore, everyone can contribute to the fight against the epidemic.
- Reducing the response time: EC with a fuzzy system can collect and process data at high speeds, which is crucial for controlling epidemic diseases that spread quickly. When an area has a few infected cases, edge services based on a fuzzy system can quickly collect the information and send the processed information to a cloud computing centre; then, the area will receive instructions for anti-epidemic requirements. The entire process will finish in a short time. In this way, large-scale outbreaks can be mostly avoided.

The advantages of EC with fuzzy systems in the medical field are shown in Table 7.

4.3.2. Framework of EC with fuzzy systems in the pandemic field

As shown in Fig. 3, we present a framework for pandemic diagnosis based on EC with a fuzzy system. This framework consists of three main parts: the data source, edge servers and cloud centre. Data sources include smart devices, smart homes, body temperature monitoring points, etc. Then, these collected data are delivered to the closest available edge server, and a preliminary diagnosis is made by a fuzzy-based diagnosis model. Notably, before the original data are transmitted to the diagnostic model, they need to be fuzzed by the fuzzy system at the data collection site or on the edge computing server. After classifying them as suspected and uninfected cases, all the suspected cases and a portion of the uninfected cases will be sent to a cloud centre for further analysis. Then, the cloud centre will send an accurate diagnosis and feedback based on a preliminary diagnosis back to edge servers. Finally, edge servers will transmit the accurate diagnosis to edge users. Meanwhile, the diagnosis model will learn by itself according to the feedback from the cloud. The feedback should follow the rules that if one case is defined as infected by a cloud centre but uninfected by edge servers, the diagnosis model will incur a higher penalty. By implementing this framework, the diagnosis model applied in edge servers will adjust and optimize itself constantly. As the number of "model parameter updates increases, the preliminary diagnosis made by edge servers will become more accurate; thus, fewer and fewer misjudged cases will be sent to the cloud centre, which will relieve the workload of the cloud. Moreover, to optimize the performance of this framework, other fuzzy-based techniques, such as the mediative fuzzy logic mathematical model for COVID-'19 prediction, can also be applied in [73]. Because both fuzzy systems and ECs could offer faster computation and quicker responses, which are essential to control pandemics, ECs with fuzzy systems will make great contributions to the control and prevention of pandemics [74] (see Fig. 5) .

Table 7
Advantages of EC with fuzzy systems in the medical field.

Advantages	Examples	References
Handling uncertain and imprecise input	Li et al. aggregated fuzzy and imprecise linguistic information by developing some geometric aggregation operators	[70]
Offering real time information	Ndii built a model that estimated the transmission rate and carrying capacity according to fuzzy rules	[71]
Using family epidemic prevention experience	Fu et al. proposed a fuzzy design method that guided the design and development of anti-epidemic products by analysing information collected from houses	[72]
Reducing the response time	Edge services based on fuzzy systems can collect information quickly and send the processed information to cloud computing centres	

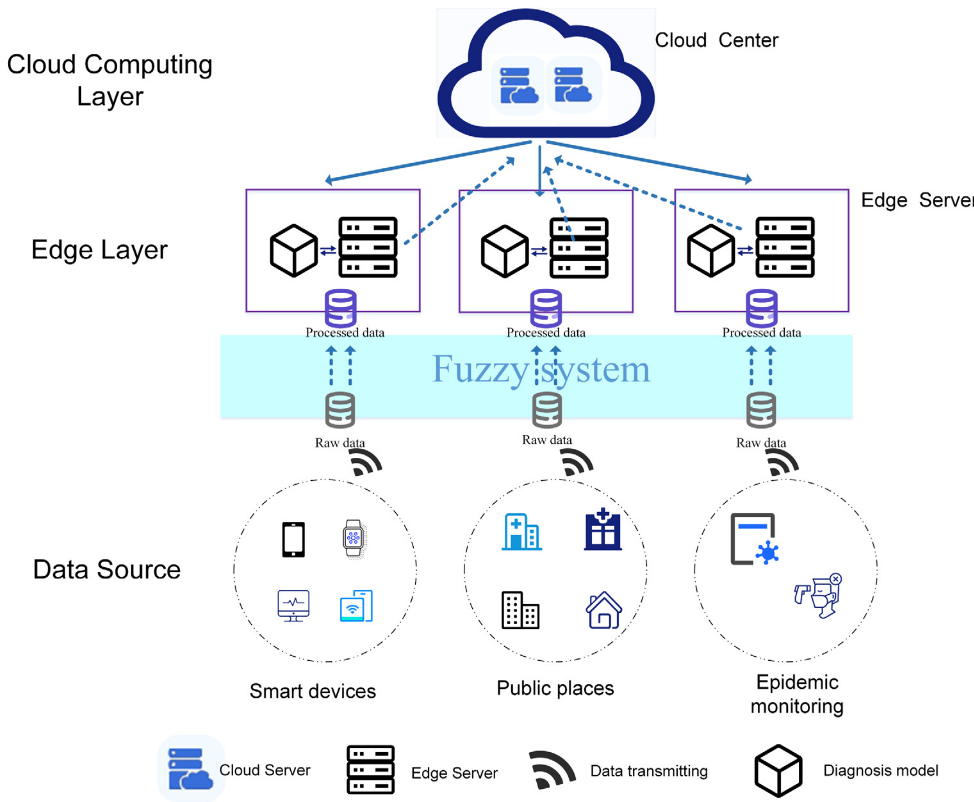

Fig. 5. Framework for EC with fuzzy systems in the pandemic field.

4.3.3. Applications of EC with fuzzy systems in the medical field

Because EC with a fuzzy system has advantages in processing massive, uncertain data and offering a quick response, current research has applied it in the medical field. The main applications are the diagnosis and prediction of diseases, remote medical treatment and the protection of medical data. The applications of EC with fuzzy systems in the medical field and its categories are listed in Table 8.

5. Future expectations and open issues

5.1. Combined with other technologies

Fuzzy logic applies fuzzy sets and fuzzy rules to control objects with strong nonlinearity and large lag, simulates the human brain, implements fuzzy comprehensive judgment, and solves regular fuzzy information problems that are difficult to address by conventional methods. Therefore, on the one hand, the combination of fuzzy logic and artificial intelligence can improve the ability of computers to judge and process data, thus reducing the computing resources consumed in data processing. On the other hand, it can make machines think according to human experience and thus become more intelligent. Moreover, existing research and experiments also suggest combining EC with fuzzy systems with other technologies. Table 9 shows some combinations of EC with fuzzy logic and other technologies and their advantages.

- Blockchain: Considered a decentralized digital ledger, the blockchain is used by many entities, and the data stored in it have the characteristics of unforgeability and transparency [63]. Therefore, the blockchain has advantages in data exchange between different entities. Abdellatif et al. [80] proposed a framework called the Medical-Edge-Blockchain (MEdge-Chain), in which EC detected and delivered adverse events at the edge quickly and the blockchain ensured that the medical information would be transmitted securely. However, because the records are stored in all the nodes in the blockchain, most of the blockchain will become increasingly larger; thus, it will overtake the high pressure of storage and computing. Moreover, the blockchain addresses the trust problem by enhancing computing power, so its performance is less prominent [81]. Because of the fuzzy system's traits of high efficiency, short delay and simple computing rules, it will play a significant role in

Table 8
The applications of EC with fuzzy systems in the medical field and its categories.

Application	Category	References
A novel diagnosis technology that can give a quick diagnosis according to the functional magnetic resonance imaging of patients and offer remote medical service	Diagnosis of diseases, Remote medical treatment	[75]
A lightweight privacy-preserving medical diagnosis mechanism based on edge computing	Diagnosis of diseases, Remote medical treatment	[76]
A modified medical diagnosis algorithm based on Pythagorean fuzzy sets	Diagnosis of diseases	[77]
A fuzzy diagnosis method based on a convolutional neural network, which uses decrypted images to classify cancer. This method resists attack securely	Protection of medical data, Diagnosis of diseases	[78]
A fuzzy diagnosis method based on a convolutional neural network, which uses decrypted images to classify cancer. This method resists attack securely	Protection of medical data, Diagnosis of diseases	[79]

facilitating efficient computation in the medical field when combined with EC and the blockchain.

- Reinforcement Learning: Reinforcement learning is unsupervised learning that benefits from continuous trial and error through interaction with the environment. As a classic machine learning (ML) method, reinforcement learning is often used to predict future data and control agents such as robots. The control precision of the agent is one of the important criteria to measure the quality of the reinforcement learning algorithm. However, in medical or mechanical engineering fields, standards for human physiological indicators and components are extremely demanding, and reinforcement learning algorithms cannot control agents to achieve such precision. The introduction of fuzzy control rules can further optimize the reinforcement learning algorithms and improve the learning ability of agents. The processing accuracy of the manipulator can be increased by embedding the experience of automatic control experts or operating technicians into reinforcement learning algorithms and connecting the bionic tools, such as the manipulator. Khalilpourazari [82] designed an algorithm based on hybrid reinforcement learning to predict COVID-19. This method optimized the choice of operators with reinforcement learning. The experimental results showed that the locally optimal solution was well avoided and that the trend of COVID-19 was accurately predicted. Similarly, Ojugo et al. proposed a smart decision maker model based on reinforcement deep learning [83]. Considering that the medical dataset frequently includes noise, ambiguities and assumptions, this model applied a deep reinforcement method to choose the best option to offer accurate classification and unambiguous results. In the field of medical treatment, Goharimanesh et al. [84] proposed a fuzzy-based reinforcement learning method that had steady and accurate performance in tracking medical robots. This model optimized the accuracy of robot control, and EC could also be used to allocate the use of medical robots to maximize the QOS. In summary, the combination of EC with a fuzzy system and reinforcement learning will be effective in medical treatment and diagnosis. By using a data separation algorithm based on reinforcement learning and computing QOS in a medical data system via fuzzy-based EC, problems of accuracy, heterogeneity and efficiency in the medical field could be addressed [85].
- Other ML Methods: In recent years, ML has become increasingly useful in the classification and diagnosis of diseases based on medical images [86]. In ML, many methods, such as neural networks and multilayer perceptrons, are used for image recognition and target detection in different scenarios. When the dataset is complete and comprehensive, these methods can often obtain more accurate results by stacking hidden layers and adjusting hyperparameters [87]. However, in the case of data loss or data segmentation, ordinary neural networks cannot achieve the desired effect through parameter optimization. Human experience can provide good solutions in such cases. In [88], Samant et al. proposed an ML technique that offered an automatic diagnosis of diabetes by using iris images. Iris images in this research were collected together; in fact, real image data may be obtained with different medical equipment, and they usually have various formats and accuracies [89]. Fortunately, a fuzzy system is effective in the addressing uncertainty. Polat et al. [90] proposed an artificial immune recognition system (AIRS) based on fuzzy weighed processing. The dataset was first weighed by fuzzy preprocessing, and then the AIRS made classifications with these processed data. The accuracy of diagnosis was satisfactory. Moreover, EC could also be applied to offer better allocation of computation resources. Taking the clustering scheme based on fuzzy logic for edge computing [91] as an example, because a fuzzy-based clustering algorithm is placed in edge servers, several biosensors can be grouped into one cluster head. Then, data will be transmitted between the cluster head and edge servers by reducing the nodes that communicate with edge servers, and the energy consumption and wastage of computing devices can be reduced significantly. In summary, applying machine learning algorithms such as clustering, logistic regression and k-nearest neighbour in EC with fuzzy systems offers a promising approach to scientific research in the medical field.

5.2. Application prospects

After summarizing the advantages of combining EC with fuzzy systems and discussing its future combination with other technologies, we proposed some possible applications in the future medical field.

- In-home health monitoring network: The development of smart devices and the Internet of Medical Things (IoMT) has pushed traditional medical treatment into smart medical services. This transformation is expected to reduce the number of people hospitalized and enables people in remote areas to receive medical services at a relatively low cost [92]. As an important part of smart medicine, in-home health monitoring networks can be realized by smart devices and medical software. In this novel medical paradigm, medical workers can take care of people with chronic illness by monitoring the data collected from wearable vital sign sensors [93], and any emergency will be responded to quickly through the application of EC. Considering that fuzzy systems have outstanding performance in the processing of medical data [94], fuzzy-based decision systems for home health care [95] and the diagnosis of diseases have been proposed. Moreover, AL-ZAHRANI proposed a method to

Table 9
Combinations of EC with fuzzy systems and other technologies and their advantages.

Technologies	Advantages	References
Blockchain	Solves the problem of security and efficient computation	[80]
Reinforcement learning	Reduces computation and enhances QoS	[85]
Other ML methods	Optimizes the allocation of computation resources and reduces energy consumption	[91]

evaluate the usability and security of medical software [96], which not only enhanced the quality of medical services but also guaranteed users' privacy.

- Smart prevention and control of the pandemic: Considering the difficult control and variability of COVID-19, prevention and control will be the norm for a long time; however, the current method still needs many people, materials and financial support. Therefore, searching for a smarter, cheaper, more efficient framework is an urgent problem. In [97], Pal et al. proposed a method to predict a country's long-term risk by using local data trends and neural networks based on fuzzy rules. Similarly, we can imitate this method to predict and grade the risk of a region, which has guiding significance for prevention and control. Ocampo et al. [98] introduced a method based on intuitionistic fuzzy (IF) sets to help decision makers determine reasonable policies for ending lockdowns. Moreover, EC can also offer a rapid response; edge servers can quickly collect, process and transmit data to cloud computation centres, which is helpful in avoiding large-scale infections when an infected case is found.

5.3. Open issues

To ensure that EC with a fuzzy system can offer high-quality service at low cost, several challenges must be overcome.

- Realize group consensus on decision-making: Through EC, patient information can be sent to different medical institutions to obtain a more accurate diagnosis. However, different experts may have different opinions, which will make it difficult to obtain a final diagnosis. Therefore, a fuzzy-based framework for weighing different points of view is required [99].
- Optimize the process of fuzzification: Because of the uncertainty of medical data, part of the membership values produced by fuzzification may make a tiny contribution to the model. Consequently, it will take more time and energy to train the model [100]. Therefore, novel feature selection and feature extraction algorithms need to be proposed to enhance the efficiency of fuzzy systems.
- Develop standardized agreements under 5G: 5G, the next generation cellular network, not only offers higher throughput and shorter latency when processing massive medical data but also makes remote medical treatment possible. To ensure that edge computing can be implemented well in 5G, it is necessary to develop a set of generally accepted rules. However, there are still challenges that need to be overcome. First, because of the flexibility of the edge cloud and diversified customization of different servers, creating a standard will be difficult. Second, a great collection of heterogeneous equipment communicates with edge clouds by different interfaces [101]. Therefore, the realization of standardized agreements under 5G needs to be addressed.
- Clarify the patient's semantics: Since different patients may provide different descriptions for their symptoms, these differences will lead to ambiguity in the diagnosis of the patients by intelligent medical systems. Current research and technology have difficulty resolving the diagnostic errors caused by subjective reasons. Thus, fuzzy logic is needed to fuzzify the user's symptom description. The future development direction is to combine fuzzy logic with machine learning to learn massive user semantic information, to determine keywords that cause ambiguity, and then to use fuzzy logic to process keywords to understand patients' semantics and thus make diagnosis more accurate.
- Ensure medical fairness: Applying fuzzy logic and edge computing in the medical field may lead to uneven medical resources if there is no reasonable guidance. Fairness is another issue that cannot be ignored in the development of new technologies. Although edge computing has improved communication in remote areas, the uneven distribution of edge servers may lead to insufficient communication resources and computing resources in these areas. Thus, it is impossible to configure a more optimized fuzzy system, and it is difficult for neural networks to perform large and precise calculations on such an edge server. In this case, despite the provision of smart medical services, the disparity between the level of medical services received by people in remote areas and those in urban areas will be exacerbated. Therefore, while improving the level of intelligent medical services, more attention should be paid to allocating computing resources to ensure the equality of medical services.
- The lack of a thorough reference model for future developments of infectious disease monitoring: As the combination of edge computing and fuzzy systems into the medical field is just emerging, there is a lack of a thorough reference model for future developments of infectious disease monitoring. Therefore, it is particularly important to propose a framework for this model. Researchers need to consider the characteristics of edge computing and fuzzy systems and the characteristics of infectious diseases, such as strong infectivity and fast spread, to design a model that can monitor infection in a timely manner. Low latency, high accuracy, low cost, and wide coverage should all be features of this model.
- The lack of annotated data: In the field of artificial intelligence, data annotation is of great significance, and weak annotation datasets often lead to deviations in experimental results. In medical surveillance, datasets are often difficult to accurately label due to the diversity of conditions and differences in individual physique. To solve this problem, data augmentation techniques, transfer learning and domain adaptation are areas that need focused attention in the future.

6. Conclusion

The goal of this paper was to comprehensively study infectious disease surveillance technologies based on fuzzy systems. The main challenges in the prediction and treatment of infectious diseases are initially listed. After a brief introduction to fuzzy systems, research on fuzzy-based infectious disease monitoring is presented. Then, we focus on the contribution of edge computing improved by fuzzy logic to the medical and intelligent fields. Finally, several open issues and future trends in infectious disease monitoring are discussed. The combination of fuzzy logic and edge computing has greatly improved existing infectious disease surveillance systems.

We find that fuzzy logic and edge computing have strong complementary effects. Edge computing provides rich data sources and data repositories for fuzzy systems, and fuzzy logic improves the computing speed and data storage efficiency of edge servers. Therefore, edge computing improved by fuzzy logic has become a more executive computing paradigm, which is responsible for data calculation and processing in the medical field. With edge computing as the carrier, fuzzy neural networks can accurately identify and process various types of medical image data to achieve accurate prediction, diagnosis and treatment. Reinforcement learning algorithms integrated with fuzzy control can improve the control precision of agents and enhance the practical operation of the robot. Fuzzy expert systems provide a rich experience base for disease detection and make the system more intelligent.

CRediT authorship contribution statement

Qinting Jiang: Conceptualization, Writing the first draft. **Xuanhong Zhou:** Writing the first draft. **Ruili Wang:** Conceptualization, Rewriting, Reviewing and editing. **Weiping Ding:** Conceptualization, Rewriting, Reviewing and editing. **Yi Chu:** Writing the first draft. **Sizhe Tang:** Writing the first draft. **Xiaoyun Jia:** Reviewing, Rewriting, Project administration. **Xiaolong Xu:** Reviewing, Rewriting, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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